Sustainability of Public Policy

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Introduction

The main objective of this course is to evaluate the effect of Public Policy changes on the budget of public entities.

- Effect of changes in electoral rules on public spending and taxation;
- Effect of participating to a Municipal Union on local expenditure;
- Effect of a centralisation of fiscal policy on local per capita current expenditure and revenue

This is a difficult task. Why?

- Causal effects $\rightarrow$ Econometric methods
- Knowledge of specialist software

Course Plan

- Part 1: Econometrics → Evaluation of Public Policy
  - Introduction to Causal Effect and Random Assignment
  - Introduction to Stata and OLS
  - Fixed Effects/Random Effects Estimations - Propensity Score Matching
  - Estimation using Stata
  - Difference in Difference
  - Estimation using Stata
- Part 2: Sustainability of Public Policies
  - Double Ballot Discontinuity Regressions
  - Paper replication

Causal Effect and Ideal World

- Other things being equal
- Counterfactual
- Randomized trial
- Quasi-experimental economics

Effect of compulsory Health Insurance on Health

- ACA (Affordable Care Act)
- ACA requires US citizens to buy HI with a tax penalty in case they don't
- Research question: does ACA improve Health?
- Americans are relatively unhealthy. USA does not have a Universal HI programme
- Is the absence of a universal HI scheme generating an health gradient?

Ceteris Paribus

- Is the health of an individual with HI any better than the health of the same person should he/she have no HI?
- Fundamental Evaluation Problem
- The same person cannot be at the same time both insured and uninsured (both treated and untreated)
- However we can use some econometric techniques that would help us get close to the solution of this problem

- NHIS(National Health Interview Survey)
- Annual Population Survey (year 2009)
- Outcome → Health: 1 poor, 2 fair, 3 good, 4 very good, 5 excellent
- Treatment: coverage by private health insurance
- Control group: Uninsured

Example taken from Angrist and Pischke "mastering 'Metrics"

Health and demographic characteristics of insured and uninsured couples

TABLE 1.1
Health and demographic characteristics of insured and uninsured couples in the NHIS

	Husbands			Wives		
	Some HI (1)	No HI (2)	Difference (3)	Some HI (4)	No HI (5)	Difference (6)
A. Health						
Health index	4.01 [.93]	3.70 [1.01]	.31 (.03)	4.02 [.92]	3.62 [1.01]	.39 (.04)
B. Characteristics						
Nonwhite	.16	.17	−.01 (.01)	.15	.17	−.02 (.01)
Age	43.98	41.26	2.71 (.29)	42.24	39.62	2.62 (.30)
Education	14.31	11.56	2.74 (.10)	14.44	11.80	2.64 (.11)
Family size	3.50	3.98	−.47 (.05)	3.49	3.93	−.43 (.05)
Employed	.92	.85	.07 (.01)	.77	.56	.21 (.02)
Family income	106,467	45,656	60,810 (1,355)	106,212	46,385	59,828 (1,406)
Sample size	8,114	1,281		8,264	1,131	

Notes: This table reports average characteristics for insured and uninsured married couples in the 2009 National Health Interview Survey (NHIS). Columns (1), (2), (4), and (5) show average characteristics of the group of individuals specified by the column heading. Columns (3) and (6) report the difference between the average characteristic for individuals

- Comparison of the average health index of insured and uninsured
- Insured individuals are healthier than uninsured ones. Being insured increases the health index of husbands of 0.31 with respect to uninsured husbands. (0.39 for wives)
- Panel B shows significant differences in average characteristics of insured and uninsured individuals (see columns 3 and 6). For example, insured are on average older, more educated and richer
- Uninsured individuals are likely not to be a good control group for insured ones

```
. reg hlth hi if fml==0 [ w=perweight ], robust
(analytic weights assumed)
(sum of wgt is   3.4119e+07)

Linear regression                               Number of obs =     9395
                                                F(  1,  9393) =    84.68
                                                Prob > F      =   0.0000
                                                R-squared     =   0.0129
                                                Root MSE      =    .9406
```

hlth	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
hi	.3132452	.0340396	9.20	0.000	.2465202	.3799702
_cons	3.695654	.0316859	116.63	0.000	3.633543	3.757765

```
. sum hlth if hi==0 & fml==0 [ aw=perweight ]
```

Variable	Obs	Weight	Mean	Std. Dev.	Min	Max
hlth	1529	4653826	3.695654	1.012124	1	5

```
. sum hlth if hi==1 & fml==0 [ aw=perweight ]
```

Variable	Obs	Weight	Mean	Std. Dev.	Min	Max
hlth	7866	29464737	4.008899	.928802	1	5

- Most variables in table 1.1 are highly correlated with both health and health insurance
- In Stata: core yedu hlth if fml==0 [aw=perweight], corr inc hlth if fml==0 [aw=perweight]
- More educated people are both more likely to be healthier and insured
- Therefore the difference in health between insured and uninsured (0.31) reflects partly the difference in education among the 2 groups

Causal Effect of Insurance on health

- Outcome of individual i = Health Index = Y_i $\rightarrow$ This is the outcome recorded in the data for individual i
- However, individual i has two potential outcomes, Y_{0i} and Y_{1i} of which only one is observed
- Y_{0i} is the potential outcome of individual i had he been uninsured, while Y_{1i} is the potential outcome of the same individual had he been insured
- The causal effect is the difference between the two potential outcomes $Y_{1i} - Y_{0i}$

TABLE 1.2
Outcomes and treatments for Khuzdar and Maria

	Khuzdar Khalat	Maria Moreño
Potential outcome without insurance: Y_{0i}	3	5
Potential outcome with insurance: Y_{1i}	4	5
Treatment (insurance status chosen): D_i	1	0
Actual health outcome: Y_i	4	5
Treatment effect: $Y_{1i} - Y_{0i}$	1	0

Example Khuzdar & Maria

- Table 1.2 is an imaginary table. Only one of the two potential outcomes is revealed.
- Khuzdar has a weak health as a starting point. Maria is a very healthy girl. Khuzdar decides to buy insurance, Maria doesn't
- The causal effect of HI for Khuzdar is $Y_{1K} - Y_{0K} = 1$. For Maria instead we have $Y_{1M} - Y_{0M} = 0$
- Khuzdar and Maria make different HI choices. Khuzdar actual health outcome is 4 and Maria's is 5. $\rightarrow Y_K - Y_M = -1$
- From this raw comparison between healthy Maria and Khuzdar we could draw up the conclusion that getting insurance is counterproductive

Example Khuzdar & Maria - Selection Bias

The comparison of the actual outcomes of Khuzdar and Maria doesn't identify a causal effect

- We therefore link observed and potential outcomes
- $Y_K - Y_M = Y_{1K} - Y_{0M}$
- If we add and subtract Y_{0K} we get
  $= Y_{1K} - Y_{0K} + Y_{0K} - Y_{0M} = (4 - 3) + (3 - 5)$
- $Y_{0K} - Y_{0M}$ is the difference in health status between Khuzdar and Maria should they both decide not to get HI.
- This term shows a lack of comparability called *Selection Bias*

Average Causal Effect

The same problem arises when we shift from individual comparisons to group comparisons

- Average Causal Effect in a group of n individuals is $Avg_n[Y_{1i} - Y_{0i}] = \frac{1}{n}\sum_{i=1}^{n}[Y_{1i} - Y_{0i}] = \frac{1}{n}\sum_{i=1}^{n}[Y_{1i}] - \frac{1}{n}\sum_{i=1}^{n}[Y_{0i}]$
- The investigation of an average causal effect begins from the comparison of the average health of insured and uninsured individuals
- The dummy variable $D_i = 1$ if i is insured and 0 otherwise
- $Avg_n[Y_i|D_i = 1] - Avg_n[Y_i|D_i = 0] =$
  $= Avg_n[Y_{1i}|D_i = 1] - Avg_n[Y_{0i}|D_i = 0]$
- In Table 1.1 we see only average Y_{1i} only for the insured and average Y_{0i} only for the uninsured.

Average Causal Effect

Assuming that HI makes everyone healthier by a constant amount $k \rightarrow Y_{1i} = Y_{0i} + k \rightarrow Y_{1i} - Y_{0i} = k$

- k is both the individual and average causal effect of insurance on health
- Substituting in $Avg_n[Y_{1i}|D_i = 1] - Avg_n[Y_{0i}|D_i = 0] \rightarrow$
  $= \{k + Avg_n[Y_{0i}|D_i = 1]\} - Avg_n[Y_{0i}|D_i = 0]$
  $= k + \{Avg_n[Y_{0i}|D_i = 1] - Avg_n[Y_{0i}|D_i = 0]\}$
- This equation shows that the comparison of insured and uninsured individuals equals the causal effect k plus the difference in average Y_{0i} of insured and uninsured
- Difference in group means= Average causal effect+Selection bias

Is the difference in means by insurance status shown in Table 1.1 affected by selection bias?

- Y_{0i} stands for all characteristics of individual i other than insurance status that are related to health
- Panel B of Table 1.1 shows that insured and uninsured individuals are different in many aspects that are related to health
- Even in an hypothetical situation where the causal effect of insurance is zero ($k = 0$), we would find that insured individuals are healthier than uninsured ones because they are on average more educated, richer, more likely to be employed...

Selection on observables

- When the only source of Selection Bias is a set of differences in observable characteristics. The identification problem is easily fixed
- We can match treatment and control group on a set of pretreatment observable characteristics
- However, in presence of many observable differences it is reasonable to expect the existence of unobserved differences

Random assignment

How does it work?

- Start with a sample of uninsured individuals
- Provide health insurance only to a random sample of them
- Compare the health of randomly selected insured individuals with the one of the uninsured
- Random assignment ensures the comparability of the two groups
- However, this last statement is true only when the groups are large enough

Law of Large Numbers

- By increasing the sample size we can ensure that the sample average gets as close as we like to the population average
- The mathematical expectation of a variable $E[Y_i]$ is the population average of this variable
- By randomly assigning individuals from the same population to treatment and control group we create two groups in a way that is similar to a repeated coin toss
- Therefore if we create a sample that is large enough we will have two groups whose average characteristics are close to those of the population
- This is true only when the groups are large enough
- These groups would be similar in any possible way even in terms of unobserved characteristics

Conditional expectation and selection bias

- The conditional expectation, $E[Y_i|D_i = 1]$, would be the average of Y_i in the population with $D_i = 1$
- If Y_i and D_i come from a random process $E[Y_i|D_i = d]$ is the average of Y_i when everyone in the population who has $D_i = d$ is sampled
- Given that randomly assigned treatment and control groups come from the same population they will be similar in every aspect including the expected Y_{0i}
- Therefore, $E[Y_{0i}|D_i = 1] = E[Y_{0i}|D_i = 0]$
- It follows that :
$E[Y_i|D_i = 1] - E[Y_i|D_i = 0] = E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0]$
$= E[Y_{0i+k}|D_i = 1] - E[Y_{0i}|D_i = 0] = k + E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0] = k$

- Randomization does not eliminate individual differences (does not transform an apple into an orange)
- It ensures that in the two groups the mix of individuals compared is the same (the 2 barrels contain the same proportion of apple and oranges)
- The first step when trying to estimate a causal effect is checking for balance between treated and control group
- This implies comparing average characteristics of treated and controls
- Random assignment is the best way to guarantee that such balance is achieved

RAND HIE

- Health Insurance Experiment ran from 1974 to 1982 and involving about 4000 people aged 14 to 61
- Participants randomly assigned to 14 different HI plans (free HI but different levels of cost-sharing)
- Research questions:
  - What's the price elasticity of health care demand?
  - Does HI lead to better health outcomes?
- Different plans: free care, coinsurance plans, deductible and catastrophic coverage

- Too many HI plans $\rightarrow$ treatment groups too small to achieve statistical significance
- Solution: grouping similar HI plans together
- First step: checking for balance $\rightarrow$ comparing pre-treatment demographic characteristics and health data

TABLE 1.3
Demographic characteristics and baseline health in the RAND HIE

	Means	Differences between plan groups			
	Catastrophic plan (1)	Deductible – catastrophic (2)	Coinsurance – catastrophic (3)	Free – catastrophic (4)	Any insurance – catastrophic (5)
A. Demographic characteristics					
Female	.560	−.023 (.016)	−.025 (.015)	−.038 (.015)	−.030 (.013)
Nonwhite	.172	−.019 (.027)	−.027 (.025)	−.028 (.025)	−.025 (.022)
Age	32.4 [12.9]	.56 (.68)	.97 (.65)	.43 (.61)	.64 (.54)
Education	12.1 [2.9]	−.16 (.19)	−.06 (.19)	−.26 (.18)	−.17 (.16)
Family income	31,603 [18,148]	−2,104 (1,384)	970 (1,389)	−976 (1,345)	−654 (1,181)
Hospitalized last year	.115	.004 (.016)	−.002 (.015)	.001 (.015)	.001 (.013)
B. Baseline health variables					
General health index	70.9 [14.9]	−1.44 (.95)	.21 (.92)	−1.31 (.87)	−.93 (.77)
Cholesterol (mg/dl)	207 [40]	−1.42 (2.99)	−1.93 (2.76)	−5.25 (2.70)	−3.19 (2.29)
Systolic blood pressure (mm Hg)	122 [17]	2.32 (1.15)	.91 (1.08)	1.12 (1.01)	1.39 (.90)
Mental health index	73.8 [14.3]	−.12 (.82)	1.19 (.81)	.89 (.77)	.71 (.68)
Number enrolled	759	881	1,022	1,295	3,198

- Reasonably good balance
- Females are less likely to be in the free insurance group compared to the catastrophic plan people
- Lower cholesterol in the free insurance group but the same group has a lower health index (poorer health)
  $\rightarrow$ No systematic differences
- How do we know that these are only chance variations?
- We exploit the tools of statistical inference

Difference in means

- Comparing averages for individuals in the treatment and control groups
- $\bar{Y}^1$ stands for $Avg_n[Y_i|D_i = 1]$ and $\bar{Y}^0$ stands for $Avg_n[Y_i|D_i = 0]$
- $\bar{Y}^1$ is therefore the Avg for n_1 observations in the treatment group and $\bar{Y}^1$ is the Avg for n_0 observations in the control group
- The sample size is $n = n_0 + n_1$
- $\bar{Y}^1 - \bar{Y}^0$ is either a causal effect if Y_i is an outcome or a check on balance if Y_i is a covariate
- We have to test whether the population mean $\mu^1 = \mu^0$ by looking at statistically significant difference in the sample averages

Difference in means

- The Standard Error for a difference in means is the sqrt of the sampling variance $V(\bar{Y}^1 - \bar{Y}^0) = V(\bar{Y}^1) + V(\bar{Y}^0) = \sigma_Y^2[\frac{1}{n_1} + \frac{1}{n_0}]$
- It follows that the Standard Error is $SE(\bar{Y}^1 - \bar{Y}^0) = \sigma_Y \sqrt{\frac{1}{n_1} + \frac{1}{n_0}}$
- In practice we have to estimate σ_Y therefore we use the estimated standard error $\hat{SE}(\bar{Y}^1 - \bar{Y}^0) = S(Y_i)\sqrt{\frac{1}{n_1} + \frac{1}{n_0}}$
- $S(Y_i)$ is the *pooled sample standard deviation*
- Under the null $\mu^1 - \mu^0 = \mu$ the *t-statistic* for a difference in means is $t(\mu) = \frac{\bar{Y}^1 - \bar{Y}^0 - \mu}{\hat{SE}(\bar{Y}^1 - \bar{Y}^0)}$
- Under the null of equal means $\mu = 0$ $t(\mu)$ equals the difference in means divided by the $\hat{SE}$ of this difference

TABLE 1.4
Health expenditure and health outcomes in the RAND HIE

	Means	Differences between plan groups			
	Catastrophic plan (1)	Deductible − catastrophic (2)	Coinsurance − catastrophic (3)	Free − catastrophic (4)	Any insurance − catastrophic (5)
A. Health-care use					
Face-to-face visits	2.78 [5.50]	.19 (.25)	.48 (.24)	1.66 (.25)	.90 (.20)
Outpatient expenses	248 [488]	42 (21)	60 (21)	169 (20)	101 (17)
Hospital admissions	.099 [.379]	.016 (.011)	.002 (.011)	.029 (.010)	.017 (.009)
Inpatient expenses	388 [2,308]	72 (69)	93 (73)	116 (60)	97 (53)
Total expenses	636 [2,535]	114 (79)	152 (85)	285 (72)	198 (63)
B. Health outcomes					
General health index	68.5 [15.9]	−.87 (.96)	.61 (.90)	−.78 (.87)	−.36 (.77)
Cholesterol (mg/dl)	203 [42]	.69 (2.57)	−2.31 (2.47)	−1.83 (2.39)	−1.32 (2.08)
Systolic blood pressure (mm Hg)	122 [19]	1.17 (1.06)	−1.39 (.99)	−.52 (.93)	−.36 (.85)
Mental health index	75.5 [14.8]	.45 (.91)	1.07 (.87)	.43 (.83)	.64 (.75)
Number enrolled	759	881	1,022	1,295	3,198

Notes: This table reports means and treatment effects for health expenditure and health outcomes in the RAND Health Insurance Experiment (HIE). Column (1) shows the average for the group assigned catastrophic coverage. Columns (2)–(5) compare averages in the deductible, cost-sharing, free care, and any insurance groups with the average in column (1). Standard errors are reported in parentheses in columns (2)–(5); standard deviations are reported in brackets in column (1).

RAND HIE results

- Individuals with a generous HI used more health care
- Inpatient admission are less price elastic than outpatient ones
- However there are no statistically significant differences in health outcomes between the different groups
- Evidence that generous health insurance can increase costs without promoting better health

RAND HIE and Oregon Trail

The RAND experiment had a few drawbacks:

- All groups had at least some HI coverage
- External validity was a concern. Today's uninsured americans are in many ways different from the HIE participants
- New experiment to check the effect of Medicaid expansion
- Medicaid currently covers families on welfare, some disabled, poor children and poor pregnant women
- The State of Oregon recently offered Medicaid(Oregon Health Plan) to randomly chosen people

Oregon Trail

- Probably the best evidence on the effects of HI on health costs and outcomes
- Lottery winners had the opportunity to apply for the OHP but they still had to demonstrate they were poor
- 75000 lottery applicants. 30000 selected to apply for OHP (treatment group). 45000 constituted the control sample

TABLE 1.5
OHP effects on insurance coverage and health-care use

	Oregon		Portland area	
Outcome	Control mean (1)	Treatment effect (2)	Control mean (3)	Treatment effect (4)
A. Administrative data				
Ever on Medicaid	.141	.256 (.004)	.151	.247 (.006)
Any hospital admissions	.067	.005 (.002)		
Any emergency department visit			.345	.017 (.006)
Number of emergency department visits			1.02	.101 (.029)
Sample size	74,922		24,646	
B. Survey data				
Outpatient visits (in the past 6 months)	1.91	.314 (.054)		
Any prescriptions?	.637	.025 (.008)		
Sample size	23,741			

Notes: This table reports estimates of the effect of winning the Oregon Health Plan (OHP) lottery on insurance coverage and use of health care. Odd-numbered columns show control group averages. Even-numbered columns report the regression coefficient on a dummy for lottery winners. Standard errors are reported in parentheses.

Oregon Trail

- 14% of lottery losers were covered by Medicaid the year after the OHP lottery
- However the probability of Medicaid coverage increased by 26% among the treatment group
- Hospital admissions increased slightly. Emergency department admissions too (perhaps counterintuitively)

TABLE 1.6
OHP effects on health indicators and financial health

	Oregon		Portland area	
Outcome	Control mean (1)	Treatment effect (2)	Control mean (3)	Treatment effect (4)
	A. Health indicators			
Health is good	.548	.039 (.008)		
Physical health index			45.5	.29 (.21)
Mental health index			44.4	.47 (.24)
Cholesterol			204	.53 (.69)
Systolic blood pressure (mm Hg)			119	−.13 (.30)
	B. Financial health			
Medical expenditures >30% of income			.055	−.011 (.005)
Any medical debt?			.568	−.032 (.010)
Sample size	23,741		12,229	

Notes: This table reports estimates of the effect of winning the Oregon Health Plan (OHP) lottery on health indicators and financial health. Odd-numbered columns show control group averages. Even-numbered columns report the regression coefficient on a dummy for lottery winners. Standard errors are reported in parentheses.

Oregon Trail

- Lottery winners have a higher probability of reporting a good health (0.039)
- This improvement derives from improved mental health (0.47)
- Physical health indicators basically unchanged
- Disappointing result for policymakers → did not generate an health dividend and increased emergency department use
- It provided a financial safety net for the poor
- However the results from Table 1.6 come from the 25% of the sample who got HI out of the lottery. But insurance status was unchanged for many winners which means that the gains were actually much larger.